Storypoint Problem Exploration - talendesb

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1 Storypoint Prediction: Problem Exploration

1.1 Problem Statement

In modern agile development settings, software is developed through repeated cycles (iterative) and in smaller parts at a time (incremental), allowing for adaptation to changing requirements at any point during a project's life. A project has a number of iterations (e.g. sprints in Scrum). Each iteration requires the completion of a number of user stories, which are a common way for agile teams to express user requirements.

There is thus a need to focus on estimating the effort of completing a single user story at a time rather than the entire project. In fact, it has now become a common practice for agile teams to go through each user story and estimate its "size". Story points are commonly used as a unit of measure for specifying the overall size of a user story.

1.2 Problem Formulation

Input: A string of length N that contains a story's name and description $C = \{c_1, c_2, c_3, ..., c_n\}$. For each story, a set of text embeddings that contains features $E = \{e_1, e_2, e_3, ..., e_m\}$ extracted from C has been provided.

Output: A natural number P associated with the story point of that user story

1.3 Dataset Information

Text Embeddings: Text embeddings are a way to convert words or phrases from text into a list of numbers, where each number captures a part of the text's meaning. The dataset has been preprocessed and converted into two kinds of text embeddings. You can choose to work with either of them or both: - Doc2Vec: Input strings are transformed into fixed-length vectors of size 128. These vectors capture the semantic meaning of words and their relationships within a document. - Look-upTable: Input strings are transformed into fixed-length vectors of size 2264. These vectors are obtained via transforming each word in the input strings into an identifier number, then padded to the length of the longest sample.

Dataset Structure & Format: Storypoint Estimation Dataset is stored in 3 folders labeled *raw data*, *look-up*, and *doc2vec*. Within each folder are 3 CSV files for training, testing, validation. Each csv file has the following columns: - `issuekey` : The unique identifier for a story. - `storypoint`: The correct number of storypoint. - An embedding column (`embedding` or `doc2vec`) contains text embedding vectors. The raw data csv will not have this and instead contain two columns with story `name` and `description`.

1.4 Exploration

1.4.1 Raw data exploration

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
```

Output exploration

[ ]:
```
# Import raw data from the CSV file

project_name = 'talendesb'

all_data = pd.concat([pd.read_csv('data/' + project_name + '/' + project_name +␣
 ↪'_train.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +␣
 ↪'_valid.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +␣
 ↪'_test.csv')])

print('Check the shape of the dataset', all_data.shape)
```

```
Check the shape of the dataset (775, 4)
```

[ ]:
```
all_data.drop(['issuekey'], axis=1, inplace=True)
all_data.head()
```

[ ]:
```
                                         title  \
0  common setup esb runtime code repositories github
1                        initial build system setup
2                                 get familar cxf
3                        service locator install
4             service locator provider registration

                                         description  storypoint
0  code repository expected setup new git github …           3
1  concept within wiki internal build system stru…           3
2  team mebers worked cxf asked get familar cxf u…           8
3  get familar install zookeeper apache hadoop su…           2
4  create cxf interceptor way could register curr…           3
```

First, let take a look at the distribution of the story point:

Interpretation of Skewness Values:

- **Skewness** > 0: Right-skewed distribution.
- **Skewness** < 0: Left-skewed distribution.

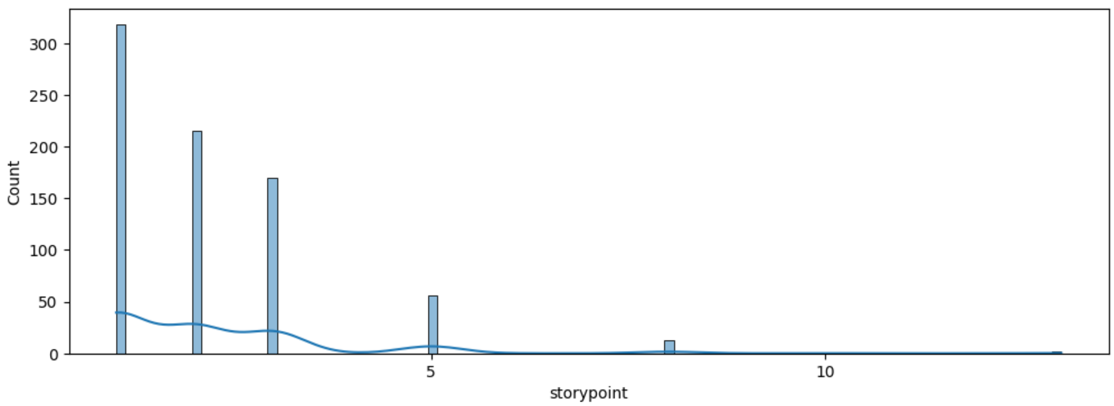
- **Skewness = 0**: Symmetrical distribution (like a normal distribution).

Interpretaion of kurtosis: - **Leptokurtic (Kurtosis > 3)**: The distribution has heavier tails and a sharper peak than the normal distribution. Data points are more likely to produce extreme values. The distribution has a higher peak and fatter tails. - **Platykurtic (Kurtosis < 3)**: The distribution has lighter tails and a flatter peak than the normal distribution. Data are fewer extreme values compared to a normal distribution. - **Mesokurtic (Kurtosis 3)**: The distribution has a similar kurtosis to the normal distribution, indicating a moderate level of outliers.

[ ]:
```python
# Draw a histogram of the story points
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(all_data['storypoint']) + 1, 5))
sns.histplot(all_data['storypoint'], bins=100, kde=True)

print('Skewness:', all_data['storypoint'].skew())
print('Kurtosis:', all_data['storypoint'].kurt())
```

```
Skewness: 2.479078195470504
Kurtosis: 9.973859400132572
```



[ ]:
```python
tmp = pd.concat([all_data['storypoint'].value_counts(),
                 all_data['storypoint'].value_counts() / all_data.shape[0] *␣
 ↪100],
                axis=1, keys=['Counts', 'Percentage (%)'])
tmp.head(20)
```

[ ]:

storypoint	Counts	Percentage (%)
1	318	41.032258
2	215	27.741935
3	170	21.935484
5	56	7.225806
8	13	1.677419
13	2	0.258065

```
10                 1         0.129032
```

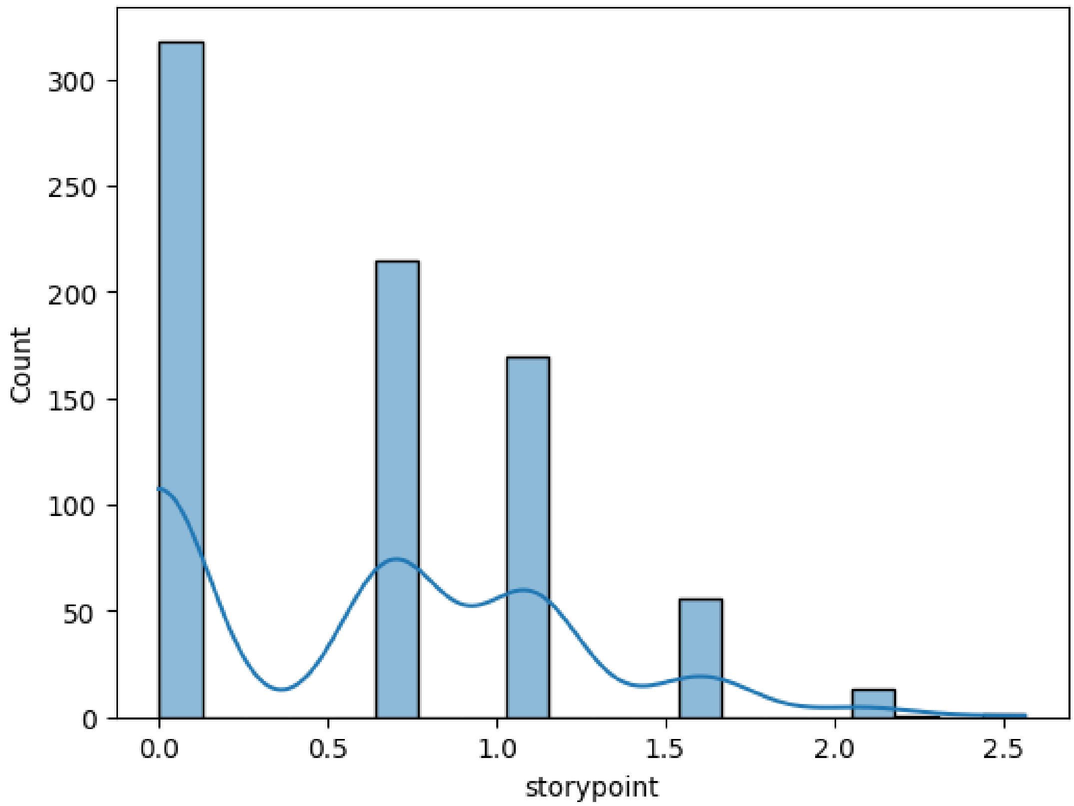
At the first sight, this data is bad. Then take a look at the statistic values, this data is even worse. Its distribution of the label is **right-skewed** and **leptokurtis**. This means if we use this to train model, the right side of the data can be the outliers and make the models become unsuable.

I will try 2 solutions: - Use log-scale on the label - Remove all the examples with label greater than a threshold (20, 30 or 40)

The first solution: logarithm magic

[ ]:
```
sns.histplot(np.log(all_data['storypoint']), bins=20, kde=True)
```

[ ]:
```
<Axes: xlabel='storypoint', ylabel='Count'>
```



[ ]:
```
print('Skewness:', np.log(all_data['storypoint']).skew())
print('Kurtosis:', np.log(all_data['storypoint']).kurt())
```

```
Skewness: 0.5277335081401946
Kurtosis: -0.4610883030775921
```

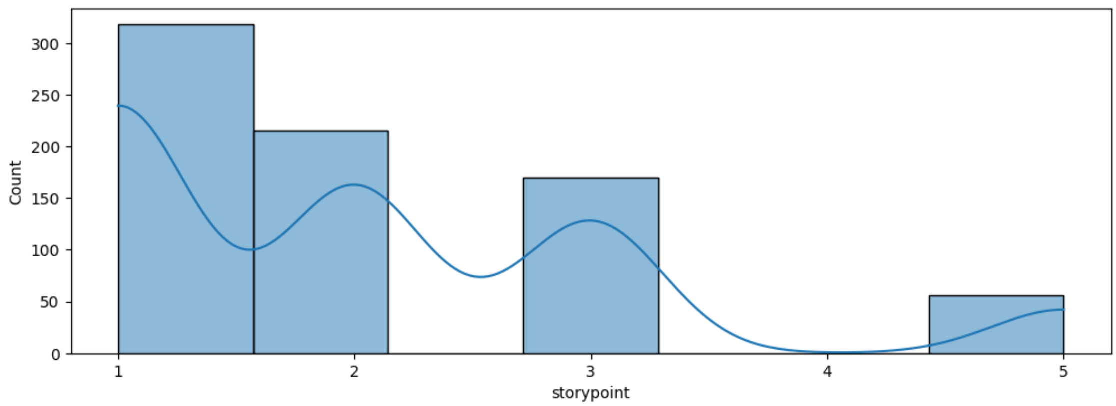
Skewness is near zero now, and the kurtosis is near 3 then before

The second solution: Dismantle and Cleave

[ ]:
```python
threshold = 7 # This threshold means that we will take all the examples with story points less than or equal to 7

new_data = all_data[all_data['storypoint'] <= threshold]
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(new_data['storypoint']) + 1, 1))
sns.histplot(new_data['storypoint'], bins=threshold, kde=True)
print('Fitered percentage: ', round(1 - new_data.shape[0] / all_data.shape[0], 2) * 100, '%')
```

```
Fitered percentage:  2.0 %
```



Input exploration The input of this problem is 2 texts: title and description. First we will find some statistics:

[ ]:
```python
title_lengths = all_data['title'].apply(lambda x: len(x.split(' ')))
print('Title analysis:')
print('   - Mean length:', round(title_lengths.mean()))
print('   - Min length:', title_lengths.min())
print('   - Max length:', title_lengths.max())

description_lengths = all_data['description'].apply(lambda x: len(x.split(' ')) if type(x) != float else 0)
print('Description analysis:')
print('   - Mean length:', round(description_lengths.mean()))
print('   - Min length:', description_lengths.min())
print('   - Max length:', description_lengths.max())
```

```
Title analysis:
   - Mean length: 6
   - Min length: 2
   - Max length: 19
Description analysis:
```

```
- Mean length: 50
- Min length: 0
- Max length: 688
```

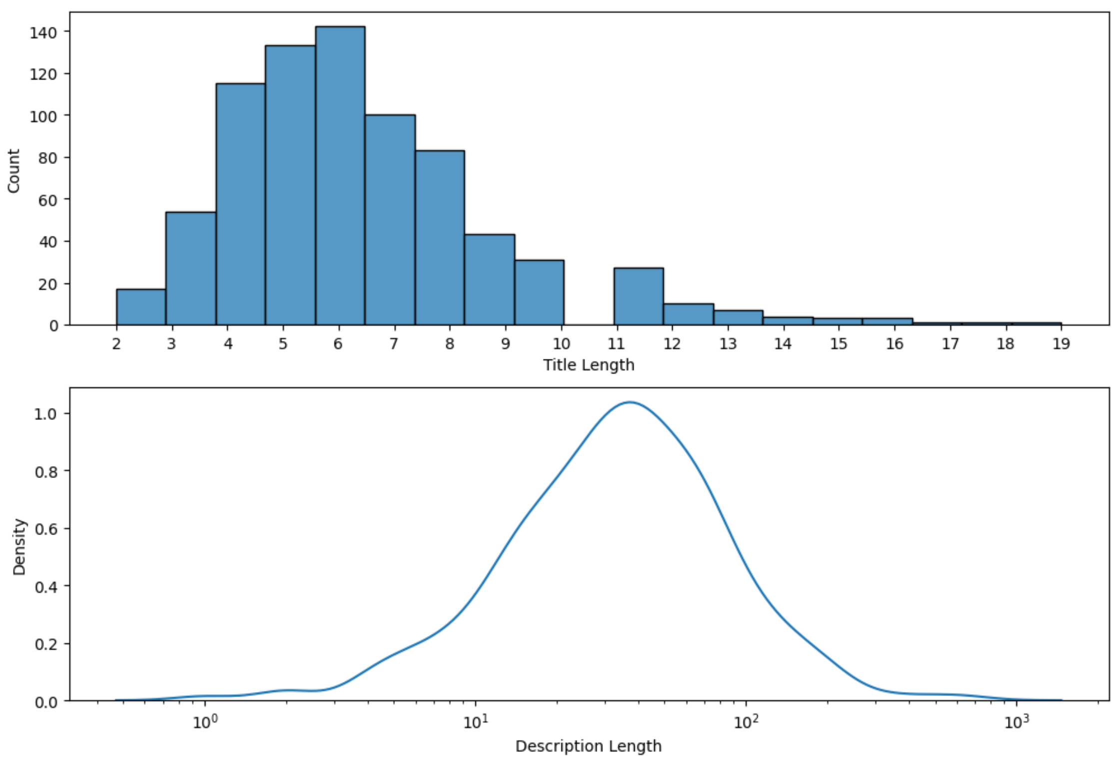
Plot the histogram of the title length and KDE of the description length (exclude 0):

[ ]:
```python
plt.figure(figsize=(12, 8))

plt.subplot(2, 1, 1)
plt.xticks(np.arange(0, max(title_lengths) + 1, 1))
plt.xlabel('Title Length')
sns.histplot(title_lengths, bins=max(title_lengths))

plt.subplot(2, 1, 2)
plt.xlabel('Description Length')
plt.xscale('log')
sns.kdeplot(description_lengths[description_lengths > 0])
```

[ ]:
```
<Axes: xlabel='Description Length', ylabel='Density'>
```



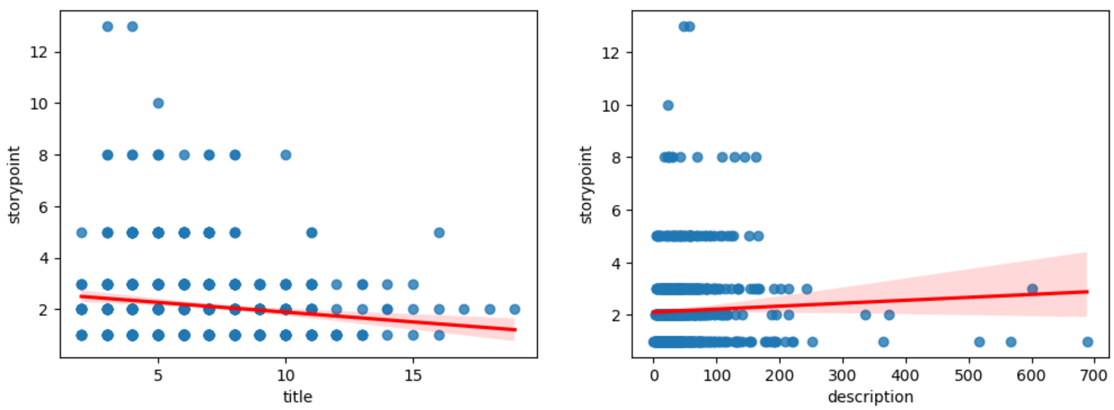
I think we should check the correlation between title length and description length:

[ ]:
```python
plt.figure(figsize=(12, 4))
```

```python
plt.subplot(1, 2, 1)
plt.xticks(np.arange(0, max(all_data['title'].apply(lambda x: len(x.split(' ')))) + 1, 5))
sns.regplot(x=all_data['title'].apply(lambda x : len(x.split(' '))),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})

plt.subplot(1, 2, 2)
sns.regplot(x=all_data['description'].apply(lambda x : len(x.split(' ')) if type(x) != float else 0),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})
```

[ ]: <Axes: xlabel='description', ylabel='storypoint'>



We can see the correlation between title and description with the storypoint through the redline. Maybe these features can help.

Let dive deeper in the input:

Title analysis:

[ ]:
```python
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data['title'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()), columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(10)
```

(1375, 2)

[ ]:

	word	frequency
170	zookeeper	1374
357	zone	1373
1195	zkserversh	1372
999	xzookeeper	1371
1099	xsdinclude	1370
1100	xsdimport	1369
673	xquery	1368
1251	xpath	1367
29	xml	1366
1231	xkms	1365

Description analysis:

[ ]:

```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data[all_data['description'].isnull() ==␣
 ↪False]['description'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
 ↪columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(20)
```

```
(6601, 2)
```

[ ]:

	word	frequency
2077	zurich	6600
1446	zubairov	6599
1355	zsolt	6598
2145	zsh	6597
5748	zoopidfile	6596
1221	zookeper	6595
5743	zookeeperserverpid	6594
2295	zookeeperserverdata	6593
3509	zookeeperor	6592
4926	zookeeperinstanceinstanceinstance	6591
2297	zookeeperdata	6590
828	zookeeperbin	6589
68	zookeeper	6588
4595	zones	6587
1555	zone	6586
5746	zkserversh	6585
204	zip	6584
5813	yuri	6583
1240	yourseldf	6582
6114	youll	6581

Yet I don't find any thing special about the words in input except so many things are bad.

1.4.2 Solving strategies

My first intuitation in this problem is that the hard part is not on the algorithm we use, it is on the **embedding** part. Therefore, in case the given embedded datasets work not properly, I will use a better embedding method which is **Bidirectional Encoder Representations from Transformers (BERT)**. Also, I will try an old way to embedding the text too: **Bag of words**.

In conclusion, I will have 4 ways to embed the text: - doc2vec (already available) - Look up (already available) - Bag Of Words - BERT

About algorithm, I will try all the regression algorithm that may give a good result:

- Ridge Regressor
- Support Vector Regressor
- Random Forest Regressor
- Gradient Boosting
- XGBoost
- Lightgbm
- Blended

Maybe, we can change the problem to the classification problem with 100 labels (desparation confirmed). In the classification problem, I will use: - Support Vector Classifier - Softmax Regression (Multinomial Logistic Regression) - Random Forest - Adaboost - XGBoost

Thanks to the libaries, the implementation of all the algorithm shrinks to its minimum form.

At last, there is still a situation that all of mentioned model don't give a good result. This gamble is thrilling (hopeless).

"But would you lose?"

Nah, I'd win.